

# **Automated Abundance Analysis of Underwater Video using Artificial Intelligence Techniques**

**By**

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requirements for the Degree of

**Doctor of Philosophy**



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## Declaration

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I, Robert Fearn, do hereby declare that this thesis contains no material that has been accepted for the award of any other degree or diploma in any tertiary institution, except by way of background information and duly acknowledged in the thesis. To the best of my knowledge and belief it contains no material previously published by another person, except where due reference is made in the text of the thesis, nor does the thesis contain any material that infringes copyright.

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## Statement of Co-authorship

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The following publications form part of the work that was undertaken for this thesis:

Fearn, R.C., Williams, R.N., Cameron-Jones, R.M., (2006) Artificial Intelligence techniques for marine video analysis. *Proc. Australian Society for Fish Biology 2006 Conference and Workshop on Cutting Edge Technologies in Fish and Fisheries Science* [Poster], 28 Aug - 1 Sept 2006, Hobart.

Mr. Robert Fearn (70%) is the primary author. He conducted the research and prepared the material for publication.

Dr. Raymond Williams (15%) and Dr. Mike Cameron-Jones (15%) of the School of Computing and Information Systems, University of Tasmania, both provided general guidance and editing as supervisor.

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## **Statement of Ethical Conduct**

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The research associated with this thesis abides by the international and Australian codes on human and animal experimentation, the guidelines by the Australian Government's Office of the Gene Technology regulator and the rulings of the Safety, Ethics and Institutional Biosafety Committees of the University.

## Abstract

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This thesis discusses research into the various factors associated with the detection, classification and tracking of commercial scallops in underwater video (from a moving camera), for the purpose of computing abundance analysis statistics. Such statistics are sought by the Tasmanian Aquaculture and Fisheries Institute (TAFI) to support the sustainable management of Tasmanian commercial scallop fisheries. The use of video is preferable in terms of environmental impact to a traditional approach such as dredging, but the partially buried nature of the scallops makes the task very challenging.

The research led to the development of a multi-stage video analysis system using a range of existing artificial intelligence techniques from the fields of computer vision and machine learning. The system comprises five main stages: instance detection, feature extraction, instance classification, motion estimation and temporal instance tracking.

This system may be required to analyse many hours of video footage. Therefore we have explored many different computer-vision-related techniques and performed numerous comparisons on these techniques in an effort to maximise system throughput without compromising the overall accuracy achieved. This includes using the University of Southern California's iLab Neuromorphic Vision C++ Toolkit (iNVT) [iLab, 2010], during the initial stages of processing, to quickly reduce the overall search space of our system down to the analysis of conspicuous or *salient* regions within the footage. In addition to this we also investigated solutions that allow our system to *skip* frames during analysis. This decreases the overall processing time as fewer frames are presented to the system, but can also adversely affect the accuracy of motion estimation. To overcome this we then use a simple and efficient outlier detection method capable of smoothing inconsistencies within the data prior to predicting instance locations in future frames.

The performance of each stage of our system has a direct impact on the performance of the remaining stages within the system. However of particular interest is the final stage which uses clustering to achieve temporal instance tracking, as it has become

evident that this stage is not only capable of tracking instances through time but is also capable of performing a second round of classification based on cluster density that plays a vital role in the elimination of false positive instances introduced in earlier stages. As a result our system performs well, being robust enough to overcome significant inconsistencies within the existing video footage provided by TAFI.



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